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EFFECTS OF REGULARIZATION CONSTRAINTS ON FMRI BRAIN NETWORK SOURCE DECOMPOSITION

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***Abstract*—Human brain functional connectivity can be reliably studied with the aid of fMRI technology. Brain functional network decomposition can be solved by available methods such as Independent Component Analysis (ICA) with independence constraint, Morphological Component Analysis with KSVD dictionary update (MCA-KSVD) with sparsity constraint on spatial components, or constraint-free method PowerFactorization (PF) that has not been applied and known to the fMRI community so far. In the quest for finding methods that are effective for analyzing fMRI functional networks, this study investigates the effects of various constraints used in the ICA, MCA-KSVD and PF methods on the resulting decomposed networks. The observed mutual effects of independence and extreme sparsity constraints experimentally suggest that there is a connection between the two constraints. Specifically, the sparsity constraint in extreme case yields spatially independent components.**

Keywords-fMRI; functional network connectivity; Independent Component Analysis; Morphological Component Analysis; K-SVD; PowerFactorization

I. INTRODUCTION

Functional human brain activity has been treated as a subject of interest to neuroscience researches. Functional Magnetic Resonance Imaging (fMRI) is a neuroimaging technique which allows one to measure neuronal activity in an indirect manner by studying local changes of blood consumption or the blood oxygen level-dependent (BOLD) contrast related to a certain synaptic activity due to a cognitive process, a motor task, or at resting-state [1–2].

With the help of fMRI, brain functional connectivity can be assessed by analyzing both the spatial and temporal interrelation among set of separate functional regions distributed over the cerebral cortex or often known as brain functional "networks" [3]. Some of common networks are visual, auditory, sensorimotor, salience, Default Mode Network (DMN), and Executive Control Network (ECN). Investigation of brain activity helps to have an insight into disease state of brain affected by disorders such as Alzheimer's, schizophrenia, depression or attention-deficit/hyperactivity disorder (ADHD) [4–7]. For instance, DMN connectivity is increased with depressed subjects [4] and decreased with ones who are affected by Alzheimer's [5] or ADHD [6]. In subjects with schizophrenia, overactivity of both DMN and ECN connectivity can be also observed [7].

The data-driven Independent Component Analysis (ICA) method is widely used by neuroscientists to discover underlying sources of fMRI activations which reveal functional connectivity patterns even in presence of noise. The component sources of ICA are assumed to be statistically independence, which means that any pair-wise collection of components has its probability equals to the product of individual probability [8–9].

PowerFactorization (PF) is a signal processing method developed to recover a missing data matrix by minimizing its rank [10–11]. To our best knowledge, PF has not been applied to fMRI. In this work, for the first time, PF is applied to decompose fMRI mixed signal into a specific quantity of meaningful functional network components without enforcing any constraint. Therefore, it could be considered as the simplest approach to the problem of brain network decomposition.

A recently developed method MCA-KSVD was proposed as an alternative method for investigating brain functional connectivity by exploiting sparse representations of spatial components. The method is a relaxation of the ICA independent-source assumption allowing only a certain maximum number of components to concurrently reside in a single voxel [12].

The link between independence and sparsity constraints has been raised in [13]. The study suggested that the mathematical design of decomposition tools for brain fMRI should emphasize other mathematical characteristics instead of independence. In the quest for finding methods that are effective for analyzing fMRI functional networks, this study aims to compare different decomposition methods in terms of effects of different regularization constraint used: no constraint, independence and sparsity constraint imposing on the spatial distribution of network components. Each of the cases is represented by specific methods: PF, ICA and MCA-KSVD, respectively. In addition, this work also experimentally confirms relation between the independence and the sparsity constraint that has been studied in [13].

II. OVERVIEW OF SELECTED METHODS

A. PowerFactorization

The PowerFactorization (PF) method attempts to analyze the fMRI data set $\boldsymbol{S}(r,t)$ as [10]

$$\boldsymbol{S} = \boldsymbol{D}\boldsymbol{X} + \boldsymbol{E}, \tag{1}$$

where $\boldsymbol{D} \in \mathbb{R}^{m\times K}$ is a full column rank matrix (with rank K) which contains temporal distributions of K decomposed brain networks; $\boldsymbol{X} \in \mathbb{R}^{K\times n}$ is a full row-rank matrix which represents spatial distributions of the corresponding networks; and $\boldsymbol{E}$ models residual noise elements.

The problem (1) is then formulated as the following optimization problem:

$$\{\hat{D}, \hat{X}\} = \arg\min_{D,X} \| S - DX \|_F . \quad (2)$$

The PF method solves the problem (2) by alternately fixing either matrix D or X and solving a linear least-squares problem to find the other matrix.

An improved version of the PF method, which guarantees better outcomes and faster convergence, uses the incremented-rank strategy. The incremented-rank PF starts with $K = 1$, then gradually increases K until a desired rank is reached [11].

B. Independent Component Analysis

The conventional approach to the brain network decomposition problem is the ICA method that follows the same decomposition as (1). ICA requires the non-Gaussianity of analyzed components. In addition, spatial ICA assumes that rows x_i of X, which imply spatial distributions of brain networks, are statistically independent:

$$P(x_1, x_2, x_3, ..., x_K) = \prod_{i=1}^{K} P(x_i), \quad (3)$$

where $P(x_i)$ is the probability of *i*-th functional network component, and $P(x_1, x_2, x_3, ..., x_K)$ is the joint probability of all components. Independence of components decomposed from ICA can be achieved by either minimizing mutual information as in Infomax algorithm or maximizing non-Gaussianity among functional network components as in FastICA algorithm [8].

C. Morphological Component Analyis using K-Singular Value Decomposition

With an over-complete dictionary D, the problem (1) can be solved with sparsity constraint by limiting the maximum number L of components simultaneously active in a voxel. The problem can be mathematically represented as [12]

$$\{\hat{D}, \hat{X}\} = \arg\min_{D,X} \| S - DX \|_F^2 \quad \text{s.t.} \quad \| x_i \|_0 \le L, \quad (4)$$

which can be solved with the K-SVD algorithm [12]. This iterative algorithm consists of two main stages: sparse encoding and dictionary updating. In the former stage, an over-complete dictionary D is initialized and the matrix X is estimated with a pursuit algorithm. In the latter stage, each column d_k is successively found and updated by the singular value decomposition. The whole procedure is repeated until the convergence is met [12].

III. Experiment Setup

A. Data Acquisition

ICA, MCA-KSVD and PF methods were applied to three fMRI data sets. The first data set was acquired by stimulating visual and auditory response of the subject. The second data set was acquired while the subject was performing working memory tasks. The third data set was acquired while the subject was in resting state. Each experiment resulted in 31 acquired brain slices whose size is 64 × 64 voxels, with TR = 2 sec and TE = 30 ms.

B. Data Simulation

To examine the effects of three decomposition methods on the acquired data sets in the presence of noise at various levels, for each data set, temporal distribution of components suspected as brain networks was extracted, which resulted in D_S [14]. The original fMRI data S was then projected on the signal subspace spanned by D_S to estimate S_S as follows:

$$S_S = D_S \left(D_S^H D_S \right)^{-1} D_S^H S. \quad (5)$$

The noise signal S_N was extracted from the data signal S as

$$S_N = S - S_S . \quad (6)$$

All correlations in the structure of the noise signal were further removed by performing the Fourier transform of S_N and randomly shuffling the phases of the obtained spectra resulting in shuffled noise data S_N'. The final simulated data set $\hat{S}$ was composed as

$$\hat{S} = S_S + \alpha S_N' , \quad (7)$$

where α controls the noise level.

ICA, MCA-KSVD and PF methods were applied on the noisy data sets to examine the effects of different regularization constraints. We used the GIFT (Group ICA of fMRI Toolbox) [15] with Infomax-based ICA method with auto-fill data reduction and values, regular stability analysis and serial group ICA to examine the independence constraint. To examine the sparsity constraint, MCA-KSVD method was used with the Orthogonal Matching Pursuit (OMP) algorithm applied in sparse encoding stage. In the experiments, for each selected method, the number of decomposed components were varied to analyze the behavior of each method. The effects of the sparsity constraint were, in addition, examined by altering the sparsity parameter L.

IV. Effects of Regularization Constraints

A. Common Effects

With the underlying constraints, some common phenomena were observed. The first phenomenon, *signal splitting*, was detected when one meaningful network existed in multiple decomposed components. This effect was observed with all ICA, MCA-KSVD and PF methods, especially when increasing K. The observed results imply that for accurate decomposition, the number of decomposed components must be chosen to agree with the underlying physiological process during the studied experiment. Fig. 1 shows some examples of signal

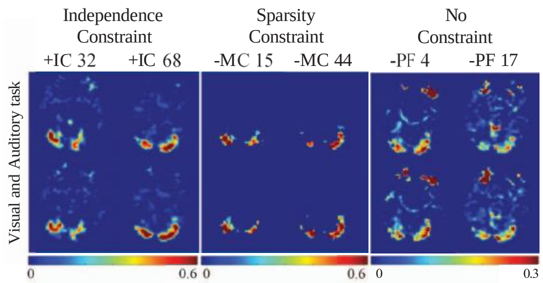

Figure 1. Signal splitting effect: Higher visual network was observed in two components of ICA, MCA-KSVD, and PF when choosing *K* to be sufficiently large.

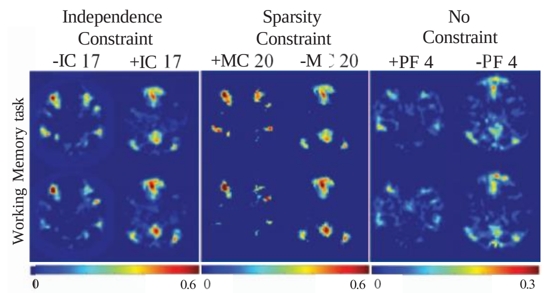

Figure 2. Signal ambiguity effect: Both DMN and salience (suspected) networks were observed when interchanging the signs of ICA, MCA-KSVD, and PF components.

splitting found when applying ICA, MCA-KSVD, and PF methods on the task-related data set.

The next phenomenon, *signal ambiguity*, was perceived when another meaningful network was observed when changing the sign of the decomposed component. This phenomenon occurred regardless of the data sets and decomposition method used, and is due to the nature of the decomposition task. Namely, changing the corresponding signs of both $\boldsymbol{D}$ and $\boldsymbol{X}$ in (1) results in the same measured data $\boldsymbol{S}$. Both suspected salience network and DMN were observed when interchanging the sign of the seventeenth ICA component, the twentieth MCA-KSVD component, and the fourth PF component, as shown in Fig. 2.

The noise tolerance of the imposed constraints was investigated, which led to the final observation that none of the applied methods showed exceptional ability to resist the influence of severe noise. Among the methods, PF yielded spatial components with the weakest signal energy. This can be explained due to the constraint-free nature of the method.

B. Independence vs. Sparsity Constraints

Besides the common effects, there were some effects specific to a certain regularization constraint. These include signal localization, signal leakage, and level of correlation among decomposed components.

Signal localization is an effect which compresses weak activations in the extracted networks and therefore, localizes the spatial distribution of the networks. Results of the MCA-KSVD method were observed to be the most localized as compared to the ICA and PF methods (see Fig. 3). The localization effect gets enhanced with the severeness of the sparsity constraint by decreasing parameter L . Fig. 4 shows the percentage of voxels with values close to zero obtained by ICA, PF and MCA-KSVD methods from the visual and auditory data set. It can be clearly seen that MCA-KSVD method with the decreased parameter L yielded the larger percentage which implied the higher localization effect. Moreover, in the specific case of resting-state data set, the sparsity constraint yielded the strongest visual network activation as compared to the constraints used in ICA and PF methods (see Fig. 5).

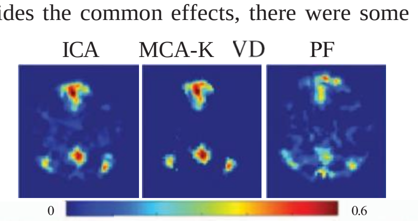

Figure 3. Signal localization: DMN component extracted by MCA-KSVD method had the most localized spatial distributions as compared to those extracted by ICA and PF.

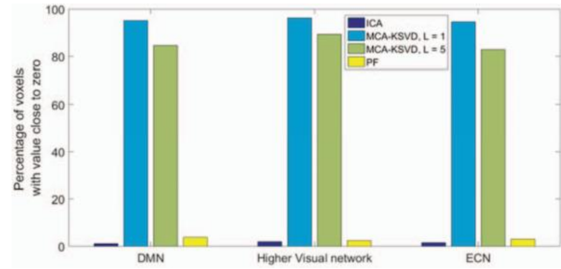

Figure 4. Signal localization: Percentage of voxels with value close to zero in DMN, Higher Visual network and ECN component extracted by ICA, MCA-KSVD and PF methods from visual and auditory stimulation data set.

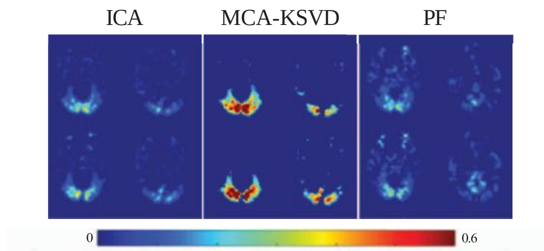

Figure 5. Visual component decomposed by ICA, MCA-KSVD and PF from resting-state data.

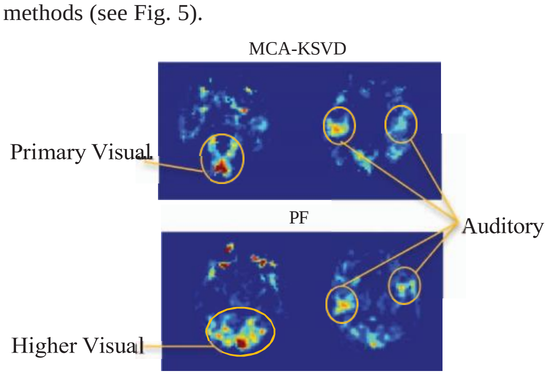

Figure 6. Signal leakage effect: Primary visual network and auditory network were observed in MCA-KSVD component with L = 8 (upper row); higher visual network and auditory network were observed in a component of PF (lower row).

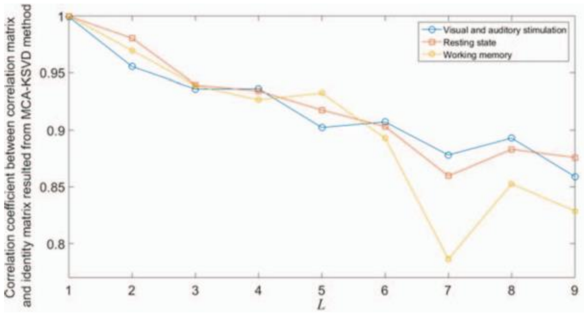

Figure 7. Similarity between the identity and correlation matrix obtainted from MCA-KSVD as a function of *L*.

Signal leakage is an undesired effect in which one component could contain more than one networks. It was observed that this effect occurred with any decomposition method but ICA and MCA-KSVD with $L = 1$. This suggests that there could be a connection between the independence and sparsity constraints.

Correlation among components was examined by correlating spatial distribution of decomposed components pair-wise. The resulting correlation matrix was then compared against the identity matrix. In general, correlation matrix obtained from ICA method had higher similarity to the identity matrix than that of MCA-KSVD. However, in all experiments, with extreme sparsity constraint, the resulting correlation matrix was found to be approaching to the identity matrix (see Fig. 7). This implies that in the case of $L = 1$, MCA-KSVD method with sparsity constraint in fact yielded uncorrelated components, similar to the case of ICA. This further confirms that there is a connection between the independence and sparsity constraints and supports the statement in [13] that a sparse and well-separated component is always nearly independent.

V. Conclusions

The effects of various regularization constraints on the ability of fMRI brain network decomposition were investigated. Amongst the investigated methods, MCA-KSVD and ICA respectively impose sparsity and independence constraints, while the PF method, which has been applied for the first time on BOLD fMRI data, was constraint-free. Experimental results showed that all three methods yielded some common effects such as signal ambiguity and signal splitting. Among the methods, PF yielded the functional networks with the weakest signal energy. The sparsity constraint produced brain functional networks that are spatially localized. A connection between sparsity and independence constraints was found by analyzing the correlation among decomposed components and the leakage effect. The results experimentally confirmed theoretical findings on the connection between the sparsity and independence constraint in [13].

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